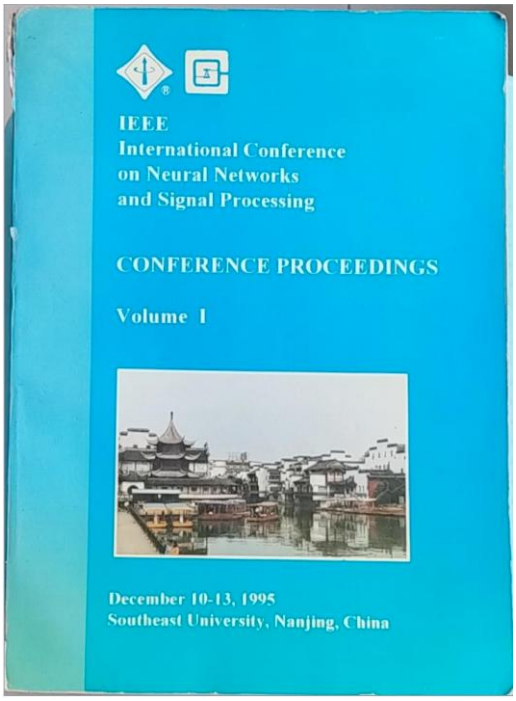

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A car shape classification based on neural networks with Non-adjacent layers connection[1]

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Abstract: Car shape recognition is a research subject of wide application. Traditional pattern recognition techniques will generally fail due to the complexity and variability of background and the vague effect of car movement. In this paper, a new classificator based on neural network, a feed-forward net with two hidden layers and with non-adjacent layer connection, is designed[1]. The net is trained with the input of the effectual features extracted from samples and the output of expected patterns. Based upon BP algorithm, error back propagation learning algorithm for the classificator is given. Experimental result shows the correctness of theoretical analysis and the good convergence of the network and is satisfactory.

Keywords: Pattern recognition, Neural network, Feature extraction

I.Introduction

In the application of pattern recognition, 2-Dimage recognition is of most interest. Car shape recognition, a typical example of 2-D image recognition, suffers from both the universal problems existed in the field of pattern recognition and the vague effect of car movement. Meanwhile, the difficulty of feature extraction is increased because of the complex and unpredictable background. Traditional pattern recognition techniques are not suited for this kind of applications. Fortunately,in recent years, much progress has been made in car industry and modernization of commutations, which stimulates the rapid development of car shape recognition techniques.

For a image whose edge feature is useful or whose feature can be its area. We can extract the edge feature of correspondent binary image to reduce information which may be too much for 2D images. In our experiment, three types of car model amounting to 103 samples are taken. The classification is performed based on edge feature extraction from binary image of the car's silhouette using auto — correlation function. Also, a discussion about the network's structural effect on recognition result is presented.

II. Prepossessing and feature extraction

1. Image prepossessing

Car samples used in our experiment are 103 black-white photos taken from three different types of real cars and from different angles. We use Threshold Curve Method[1] for binary processing of image, Adaptive Smoothing Technique[2] for elimination of noise, Roblinson Operator[3] for edge detection and Doutch Technique[4] for edge thinning. The details are not discussed here. Interested readers can refer to [1],[2],[3]and [4].

2. Feature extraction[5]

The basic principle for feature extraction of car patterns requires three properties:

i.translation invariance;
ii.scale invariance;
ii.rotation invariance.

In general, two types of features can be extracted for pattern recognition;

i.structural feature;
ii.mathematical model feature.

We choose the second type of feature and the auto-correlation function values as the input of the network.

[1] Called Net95 in this resubmission in Aug. 2025

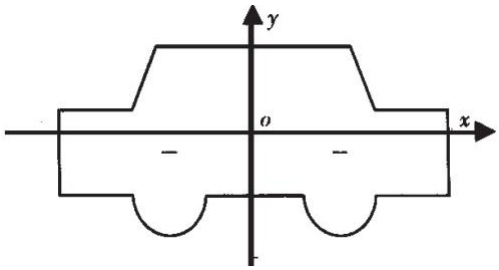


Fig.1

Suppose that I is a binary image in XOY plane, the centre of gravity of car silhouette is taken as the origin of XOY coordinate system (shown in Fig.1). f(x,y) is a binary function defined in XOY plane.

$$f(x,y) = \begin{cases} 1 & \text{for } (x,y) \in I \\ 0 & \text{for } (x,y) \in \bar{I} \end{cases} \quad (1)$$

Obviously, the area of I, can be

$$A = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)dxdy$$

We can define

$$g(u,v) = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+u,x+v)dxdy \quad (2)$$

Where g(u.v) is the auto-correlation function of f(x,y). Geometrically, g(u,v) represents the area of overlapped region by 1(u,v) and 1(0.0), with 1(0,0) being the original image and I(u,v) the translated one of the original from (0, 0) to (u, v) (shown in Fig.2).

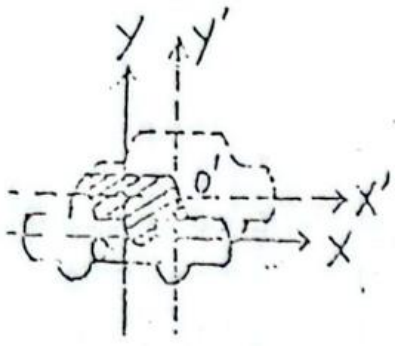


Fig. 2

Then, we obtain the standard auto-correlation function,

$$G_0(u,v) = \frac{g(u,v)}{A} = \frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+u,x+v)dxdy}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)dxdy} \quad (3)$$

As can be easily seen, G0(u,v) is both translation invariant and scale invariant, but not rotation invariant. For this reason, we can discretize $G_0(u,v)$ under the polar coordinate system (r,θ). The circular property with respect to d of the discrete values eliminates the sensitiveness of image feature produced by image rotation. Let

$$\begin{aligned} u &= a\sqrt{A}\cos\theta \\ v &= a\sqrt{A}\sin\theta \end{aligned} \quad (4)$$

Substituted with (4), (3) can ben rewritten as

$$G(a,\theta) = G_0(a\sqrt{A}\cos\theta, a\sqrt{A}\sin\theta)$$

$$= \frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+a\sqrt{A}\cos\theta, x+a\sqrt{A}\sin\theta)dxdy}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)dxdy} \quad (5)$$

From (5), we can easily verify the following relation:

$$G(a, \theta+\pi) = G(a,\theta) \quad (6)$$

That is to say, $G(a,\theta)$ is periodic with π with respect to θ. Consequently, our consideration can limited to $\theta \in [0,\pi)$. Let

$$a = a_i, \qquad j=1,2,\ldots, M \quad (7)$$

$$\theta = \theta_j(j-1)\pi/N, \qquad j=1,2,\ldots, N \quad (8)$$

Where M is quantitation granule of polar radius and θ the rotation angle.

Subsituting (5) with (7) and (8), we can obtain discrete values of G(a, G) which can be regarded as the feature of image I. The feature vector of I is given by

$$F_c = [G(a_1,\theta_1), G(a_2,\theta_2), \ldots, G(a_M,\theta_N)]^T \quad (9)$$

Based on the above, 103 sample patterns are taken and a 12 (M=3, N=4) dimension feature vector is constructed for each. Then, 48 sample patterns are randomly picked out as training set from three types of samples and the rest makes up the testing set. The training set and the testing one are used for the network's train and test respectively.

III. Neural network classificator

Neural network classificator is a non-linear dynamic system which can be applied to solve the problems with complex environment information, indefinite background knowledge and reasoning rules. It tolerates the great loss and distortion of samples. The neural network classifier will classify an unknown pattern as the most recently retained one by training with the samples and retaining the results.

1. The structure of neural network

Fig.3 shows the topological structure of the network designed in our work. Table 1 gives the detailed information of it.

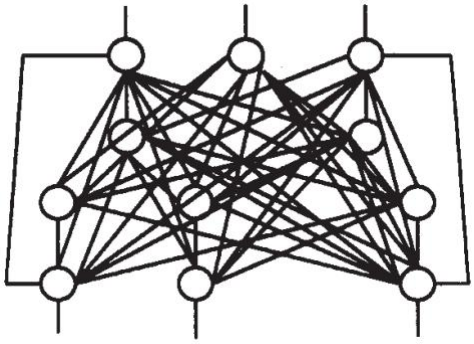


Fig. 3 Topological structure of netwok

correspondingly. Let XKi represents the input of the ith node in the Kth layer and YKj the output of the same node in the same layer. Let WKLij denotes the connecting weight between the ith node in the Kth layer and the jth node in the Lth layer, θ_{Ki} the threshold of the ith node in the Kth layer and NL the number of node in the Lth layer. Thus, we have

$$\begin{cases} Y_{Ki} = X_{Ki} & \text{for } K = 1 \\ Y_{Ki} = f\left(\sum_{L=1}^{K-1}\sum_{j=1}^{N_L} W_{KLji}\, Y_{Lj} + \theta_{Ki}\right) & \text{for } K > 1 \end{cases} \quad (10)$$

Table 1 Detailed information of neural network

layer order	layer name	number of nodes	connection				activation function	learning rule	initial scope of weight
			1	2	3	4			
1	input	12	/	/	/	/	/	/	/
2	hidden 1	16	all	/	/	/	sigmoid	delta	[-0.1,0.1]
3	hidden 2	6	all	all	/	/	sigmoid	delta	[-0.1,0.1]
4	output	3	all	all	all	/	sigmoid	delta	[-0.1,0.1]

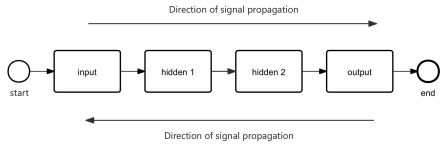


Fig.4 Circuit model of general BP net

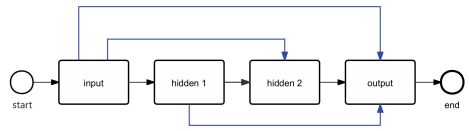


Fig.5 Circuit model of net in our design

2. Algorithm of neural network

General BP network, with adjacent layer all connection or local connection, can be equivalent to a biological circuit model of series connection (shown in Fig.4). But in our design, the network with non-adjacent layer connection can be equivalent to a biological circuit model of both series and parallel connection (shown in Fig.5, "→" represents neural fibre and "□" neural node group).

Because we introduce such model as shown in Fig.5, the sum function and the formula for computing correction parameter of BP algorithm will change

Where $f(*) = \frac{1}{1+e^{-*}}$. The deduction of correspondent formula for computing error back propagation and connectiong weight is given below.

Let E_P be error function in output layer when the network is fed with pattern pair (XP, YP), it be given by

$$E_P = \frac{1}{2}\sum_{j=1}^{N_P} (\bar{Y}_{Tj} - Y_{Tj})^2 \quad (11)$$

Where $\bar{Y}_{Tj}$ is the expected output of the jth output layer node, Y_{Tj} is the real output of it. N_P is the number of output layer nodes. $\sum E_P$ is the total error accumulated by all sample patterns in the training set.

Let, $$\text{net}\, Y_{Kj} = \sum_{L=1}^{K-1}\sum_{i=1}^{N_L} W_{KLji}\, Y_{Li} \quad (12)$$

be the input sum function of the jth node in the Kth layer. The real output of it is designated by (10) and f(*) is differentiable and non-decreased progressively. For node j in layer K, the general error is defined as

$$e_{Kj} = -\frac{\partial E_P}{\partial \text{net}\, Y_{Kj}} = -\frac{\partial E_P}{\partial Y_{Kj}} \cdot \frac{\partial Y_{Kj}}{\partial \text{net}\, Y_{Kj}} = -\frac{\partial E_P}{\partial Y_{Kj}} \cdot f'(\text{net}\, Y_{Kj}) \quad (13)$$

If K=P, for output layer node, from (11) we can have

$$\frac{\partial E_P}{\partial Y_{Kj}} = \frac{\partial}{\partial Y_{Pj}}\left[\frac{1}{2}\sum_{j=1}^{N_P} (\bar{Y}_{Pj} - Y_{Pj})^2\right] = -(\bar{Y}_{Pj} - Y_{Pj}) \quad (14)$$

Substituted with (13), (14) can be rewritten as

$$e_{Pj} = (\bar{Y}_{Pj} - Y_{Pj})\, f'(\text{net}\, Y_{Pj}) \quad (15)$$

If K<P, for hidden layer node, we have ,

$$\frac{\partial E_P}{\partial Y_{Kj}} = \sum_{L=K+1}^{P}\sum_{i=1}^{N_L}\frac{\partial E_P}{\partial \text{net } Y_{Li}} \cdot \frac{\partial \text{net } Y_{Li}}{\partial Y_{Kj}}$$

$$= \sum_{L=K+1}^{P}\sum_{i=1}^{N_L} e_{Li} \cdot \frac{\partial \sum_{K=1}^{L-1}\sum_{i=1}^{N_K} W_{LKji}\, Y_{Ki}}{\partial Y_{Kj}}$$

$$= \sum_{L=K+1}^{P}\sum_{i=1}^{N_L} e_{Li}\, W_{LKij} \qquad (16)$$

Substituted with (16), (13) can be rewritten as

$$e_{Kj} = f'(\text{net } Y_{Kj}) \sum_{L=K+1}^{P}\sum_{i=1}^{N_L} e_{Li}\, W_{LKij} \qquad (17)$$

(17) can be regarded as error propagated from all nodes of former (P → K) layers to all nodes of Kth layer. To reduce the error function E_P, we adjust the connecting weight using Gradient Descent Method based upon the original connecting weight W_{LKij} :

$$\Delta W_{KLj} = -a\frac{\partial E_P}{\partial W_{KLj}} = -a\frac{\partial E_P}{\partial \text{net } Y_{Ki}} \cdot \frac{\partial \text{net } Y_{Ki}}{\partial W_{KLj}}$$

$$= -a\, e_{Ki} \cdot \frac{\partial \sum_{L=1}^{K-1}\sum_{j=1}^{N_L} W_{KLij}\, Y_{Lj}}{\partial W_{KLij}} = a\, e_{Ki} \cdot Y_{Lj} \qquad (18)$$

Where a is learning rate ($0 < a < 1$), e_{Ki} is expressed by (17) and Y_{Lj} is the output of the jth node in the Kth layer.

From above deduction, it can be seen that the sum function is significantly increased and f(·) is rapidly trends to be stable by this kind of connection. Furthermore, the learning process is accelerated. Although the increase of multiply and add operation times, the computational cost of activation function f(·) is greatly reduced and the model designed in our work is more similar to biological neural network structure. Experiment reveals the correctness of our analysis. Compared with general BP network, the network designed in our experiment have a good convergence and satisfactory recognition ratio is obtained.

IV. Experiment and discussion

The neural network shown in Fig.3 is a highly reliable structure which has been designed through many experiments over and over again.The classificator is trained 500,000 times with 48 training samples and tested with 55 testing samples. The experimental results are shown in Table 2.

Table 2 Experiment results

set type	number of samples	wrong recognition ratio	refusive recognition ratio	right recognition ratio
training set	48	0	0	100%
test set	55	0	5.55%	94.45%

In order to reduce wrong-recognition ratio to the greatest extent, an appropriate judge function is chosen to increase the refusive-recognition ratio. If 1.85% wrong-recognition ratio is allowed, the right recognition ratio will increase to 98.65%. Note: our formula for computing recognition ratio is given by

$$R = \frac{\text{Number of correctly recognized testing samples}}{\text{Total Number of testing samples}} \qquad (19)$$

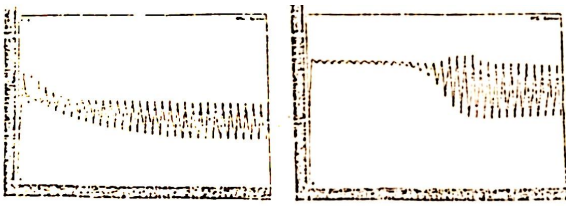
Table 3 Experimental results for general BP net

set type	number of samples	training times	wrong recognition ratio	refusive recognition ratio	right recognition ratio
training set	48	50,000	3/48 = 6.3%	1/48=2.1%	91.6%
		100,000	2/48=4.2%	1/48=2.1%	93.7%
		150,000	2/48=4.2%	1/48=2.1%	93.7%
test set	55	50,000	3/55=5.6%	5/55=9.1%	85.3%
		100,000	3/55=5.6%	5/55=9.1%	85.3%
		150,000	2/55=3.6%	7/55=12.7%	83.7%

To verify the advantages of network designed in our work, a comparison experiment is carried out between general BP feed-forward propagation net and ours. The number of layers and nodes in each corresponds to what is shown in Fig.3, but there is no non-adjacent layer connection. Table 3 shows the results.

As can be seen from the experimental results, when certain training time is reached, dependability of the network on samples in testing set is increased, which results in the increase of recognition ratio of samples in training set and the decrease of recognition ratio of samples in testing set.

Fig.6.a and Fig.6.b gives the mean-square-error curve in the former 16,000 trains for the two types of network.



(a) Net95 in our experiment (b) General BP net

Fig. 6 Curves for mean square error

V. Conclusion

In this paper, a new way cf weight connection is adopted and a new algorithm for error back propagation is deduced based upon general BP algorithm. Our network has an excellent performance and a rapid convergence speed which is noticeably superior to general BP network. Satisfactory results is obtained in our application to car shape recognition. Though our basic idea about learning algorithm inherits that about traditional BP algorithm and local minimization problem is not satisfactorily solved,our research work, as an application technology, is of great importance to theoretical study on neural network and development of pattern recognition techniques.

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Car Shape Classification Based on Neural Network with Non—adjacent Layer Connection

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ii. scale invariance;

iii. rotation invariance.

In general, two types of features can be extracted for pattern recognition:

i. structural feature;

ii. mathematical model feature.

We choose the second type of feature and the auto—correlation function values as the input of the network.

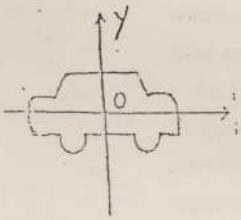


Fig. 1

Suppose that I is a binary image in XOY plane, the centre of gravity of car silhouette is taken as the origin of XOY coordinate system (shown in Fig. 1). $f(x,y)$ is a binary function defined in XOY plane

$$f(x,y)=\begin{cases}1 & for\ (x,y)\in I\\ 0 & for\ (x,y)\overline{\in} I\end{cases}\quad(1)$$

Obviously, the area of I, can be

$$A=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}f(x,y)dxdy\ .$$

we can define

$$g(u,v) = f(x,y) \circ f(x,y)$$
$$= \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+u,y+v)dxdy \quad (2)$$

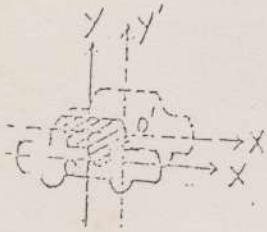


Fig. 2

Where g(u,v) is the auto—correlation function of f (x,y). Geometrically, g (u,v) represents the area of overlapped region by I (u,v) and I(0,0), with I (0,0) being the original image and I (u, v) the translated one of the original from (0,0) to (u,v) (shown in Fig. 2).

Thus, we obtain the standard auto—correlation function

$$G_0(u,v) = \frac{g(u,v)}{A}$$
$$= \frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+u,y+v)dxdy}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)dxdy} . \quad (3)$$

As can be easily seen, $G_0(u,v)$ is both translation invariant and scale invariant, but not rotation invariant. For this reason, we can discretize $G_0(u,v)$ under the polar coordinate system (r,θ). The circular property with respect to θ of the discrete values eliminates the sensiveness of image feature produced by image rotation.

Let

$$u = a\sqrt{A}\cos\theta$$
$$v = a\sqrt{A}\sin\theta . \quad (4)$$

Substituted with (4), (3) can be rewritten as

$$G(a,\theta) = G_0(a\sqrt{A}\cos\theta, a\sqrt{A}\sin\theta)$$
$$= \frac{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)f(x+a\sqrt{A}\cos\theta, y+a\sqrt{A}\sin\theta)dxdy}{\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} f(x,y)dxdy} . \quad (5)$$

From(5), we can easily verity the following relation:

$$G(a,\theta+\pi) = G(a,\theta) . \quad (6)$$

That is to say, G(a,θ) is periodic with π with respect to θ. Consequently, Our consideration can be limited to $\theta \in [0,\pi)$.

Let

$$a = a_i, i = 1,2,\cdots,M \quad (7)$$
$$\theta_j = \theta_j(j-1)\pi/N, j = 1,2,\cdots,N \quad (8)$$

where M is quantilization granule of polar radius and θ the rotation angle.

Substituting (5) with (7) and (8), we can obtain discrete values of $G(a_i,\theta_j)$ which can be regarded as the feature of image I. The feature vector of I is given by

$$F_c = [G(a_1,\theta_1), G(a_2,\theta_2)\cdots, G(a_M,\theta_N)]^T \quad (9)$$

Based on the above, 103 sample patterns are taken and a 12(M=3,N=4) dimension feature vector is constructed for each. Then, 48 sample patterns are randomly picked out as training set from three types of samples and the rest makes up the testing set. The training set and the testing one are used for the network's train and test respectively.

Ⅲ. Neural network classificator

Neural network classificator is a non—linear dynamic system which can be applied to solve the problems with complex environment information, indefinite background knowledge and reasoning rules. It tolerates the great loss and distortion of samples. The neural network classificator will classify an unknown pattern as the most recently retained one by training with the samples and retaning the results.

1. the Structure of neural network

Fig. 3 shows the topological structure of the network designed in our work. Table gives the detailed information of it.

2. Algorithm of neural network

General BP network, with adjacent—layer all connection or local connection, can be equivalent to a biological circuit model of series connection(shown in Fig. 4). But in our design, the network with non—adjacent layer connection can be equivalent to a biological circuit model of both series and parallel connection(shown in Fig. 5, "→" represents neural fibre and "□" neural node group).

Because we introduce such model as shown in fig. 5, the sum function and the formula for computing correction parameter of BP algorithm will chang correspondently. Let X_{Ki} represents the input of the ith node in the Kth layer and Y_{Ki} the output of the same node in the same layer. Let W_{KIij} denotes the connecting weight between the ith node in the Kth layer and the jth node in the Lth layer, θ_{Ki} the threshold of the ith node in the Kth layer and N_i the number of node in the Lth layer. Thus, we have

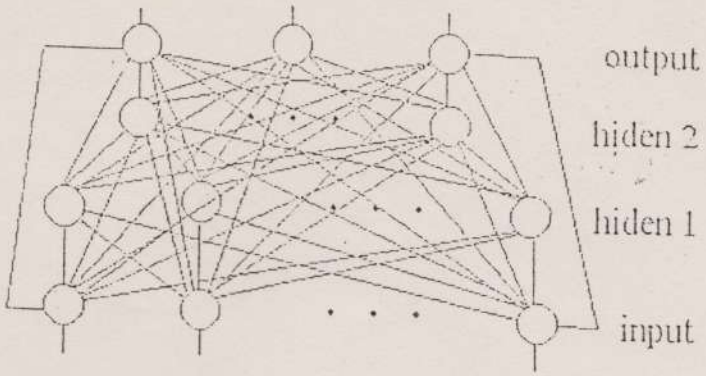


Fig. 3 Topological structure of network

layer order	layer name	number of nods	connection 1	2	3	4	activation function	learning rule	initial scope of weight
1	input	12	/	/	/	/	/	/	/
2	hiden 1	16	all	/	/	/	sigmoid	delta	[−0.1,0.1]
3	hiden 2	6	all	all	/	/	sigmoid	delta	[−0.1,0.1]
4	output	3	all	all	all	/	sigmoid	delta	[−0.1,0.1]

Table 1 Detailed information of neural network

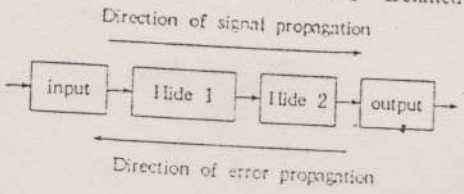


Fig. 4 Circuit model of general BP net

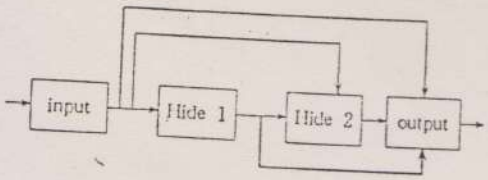


Fig. 5 Circuit model of net in our design

$$\begin{cases} Y_{Ki} = X_{Ki} & for\ K=1 \\ Y_{Ki} = f\left(\sum_{L=1}^{K-1}\sum_{j=1}^{N_L} W_{KLij}Y_{Lj} + \theta_{Ki}\right) & for\ K>1 \end{cases} \quad (10)$$

where

$$f(\cdot) = \frac{1}{1+e^{-(\cdot)}}.$$

The deduction of the correspondent formula for computing error back propogation and connecting weight is given below.

Let E_P be error function in output layer when the network is fed with pattern pair (X_P, Y_P), it can be given by

$$E_P = \frac{1}{2}\sum_{j=1}^{N_P}(\bar{Y}_{Tj} - Y_{Tj})^2 \quad (11)$$

where $\bar{Y}_{Tj}$ is the expected output of the jth output layer node, Y_{Tj} is the real output of it. N_P is the number of output layer nodes. $\sum E_P$ is the the total error accumulated by all sample patterns in the training set.

Let

$$netY_{Kj} = \sum_{L=1}^{K-1}\sum_{i=1}^{N_L} W_{KLji}Y_{Li} \quad (12)$$

be the input sum function of the jth node in the Kth layer. The real output of it is designated by (10) and $f(\cdot)$ is differentiable and non−decreased progressively. For node j in layer K, the general error is defined as

$$\begin{aligned} e_{Kj} &= -\frac{\partial E_P}{\partial netY_{Kj}} \\ &= -\frac{\partial E_P}{\partial Y_{Kj}} \cdot \frac{\partial Y_{Kj}}{\partial netY_{Kj}} \\ &= -\frac{\partial E_P}{\partial Y_{Kj}} \cdot f'(netY_{Kj}) . \end{aligned} \quad (13)$$

If K=P, for output layer node, from(11) we can have

$$\frac{\partial E_p}{\partial Y_{Kj}} = \frac{\partial}{\partial Y_{Pj}}\left[\frac{1}{2}\sum_{j=1}^{N_P}(T_{Pj}-Y_{Pj})^2\right]$$
$$= -(T_{Pj}-Y_{Pj}). \quad (14)$$

Substituted with(13), (14) can be rewritten as

$$e_{Pj} = (T_{Pj}-Y_{Pj})f'(netY_{Pj}). \quad (15)$$

If K<P, for hiden layer node, we have

$$\frac{\partial E_p}{\partial Y_{Kj}} = \sum_{L=K+1}^{P}\sum_{i=1}^{N_L}\frac{\partial E_p}{\partial netY_{Li}}\cdot\frac{\partial netY_{Li}}{\partial Y_{Kj}}$$
$$= \sum_{L=K+1}^{P}\sum_{i=1}^{N_L}e_{Li}\left[\frac{\partial\left(\sum_{k=1}^{L-1}\sum_{i=1}^{N_k}W_{Lik}Y_{ki}\right)}{\partial Y_{Kj}}\right]$$
$$= -\sum_{L=K+1}^{P}\sum_{i=1}^{N_L}e_{Li}W_{LKij}. \quad (16)$$

Substitued with (16), (13) can be rewritten as

$$e_{Kj} = f'(netY_{Kj})\sum_{L=K+1}^{P}\sum_{i=1}^{N_L}e_{Li}W_{LKij}. \quad (17)$$

(17) can be regarded as error propogated from all nodes of the former (P−K) layers to all nodes of the Kth layer.

To reduce the error function E_p, we adjust the connecting weight using Gradient Descent Method based upon the original connecting weight W_{KIj}:

$$\Delta W_{KIj} = -\alpha\frac{\partial E_p}{\partial W_{KIj}}$$
$$= -\alpha\frac{\partial E_p}{\partial netY_{Ki}}\cdot\frac{\partial netY_{Ki}}{\partial W_{KIj}}$$
$$= \alpha e_{Ki}\cdot\frac{\partial\sum_{l=1}^{K-1}\sum_{j=1}^{N_L}W_{KIj}Y_{Lj}}{\partial W_{KIj}}$$
$$= \alpha e_{Ki}\cdot Y_{Lj} \quad (18)$$

where α is learning rate (0<α<1), e_{Ki} is expressed by (17) and Y_{Lj} is the output of the jth node in the Kth layer.

From above deduction, it can seen that the sum function is significantly increased and f(·) is rapidly trends to be stable by this kind of connection. Furthermore, the learning process is accelerated. Although the increasement of multiply and add operation times, the computational cost of activation function f(·) is greatly reduced and the model designed in our work is more similar to biological neural network struture. Experiment reveals the correctness of our analysis. Compared with general BP network, the network designed in our experiment have a good convergence and satisfactory recognition ratio is obtained.

Ⅳ. Experiment and discussion

The neural network shown in Fig. 3 is a highly reliable structure which has been designed through many experiments over and over again. The classificator is trained 500,000 times with 48 training samples and tested with 55 testing samples. The experimental results are shown in Table 2.

set type	number of samples	wrong—recognition ratio	refusive—recognition ratio	right—recognition ratio
training set	48	0.0%	0.0%	100%
testing set	55	0.0%	5.55%	94.45%

Table 2 Experimental results

In order to reduce wrong—recognition ratio to the greatest extent, an appropriate judge function is chosen to increase the refusive—recognition ratio. If 1.85% wrong—recognition ratio is allowed, the right recognition ratio will increase to 98.65%. Note: our formula for computing recognition ratio is given by

$$R = \frac{\text{Number of correctly recognized testing samples}}{\text{Total number of testing samples}}. \quad (19)$$

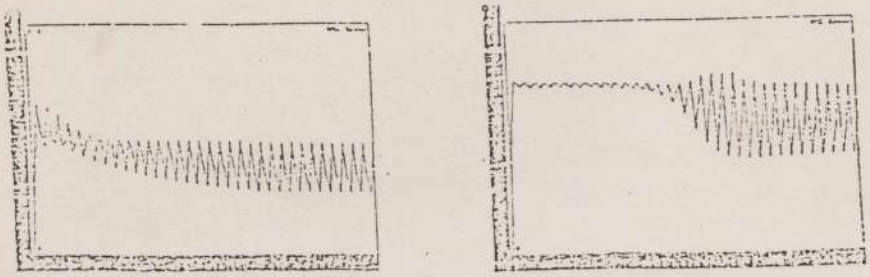
To verify the advantages of network designed in our work, a comparison experiment is carried out between general BP feed—forward propogation net and ours. The number of layers and nodes in each corresponds to what is shown in Fig. 3, but there is no non—adjacent layer connection. Fig. 3 shows the results.

As can be seen from the experimental results, when certain training time is reached, dependability of the network on samples in testing set is increased, which results in the increasement of recognition ratio of samples in trainng set and the decreasement of recognition ratio of samples in testing set.

Fig. 6. a and Fig. 6. b gives the mean—square—error curve in the former 16,000 trains for the two types of network.

set type	number of samples	training times	wrong — recognition ratio	refusive—recognition ratio	right—recognition ratio
traing set	48	50,000	$\frac{3}{48}=6.3\%$	$\frac{1}{48}=2.1\%$	91.6%
		100,000	$\frac{2}{48}=4.2\%$	$\frac{1}{48}=2.1\%$	93.7%
		150,000	$\frac{2}{48}=4.2\%$	$\frac{1}{48}=2.1\%$	93.7%
testing set	55	50,000	$\frac{3}{55}=5.6\%$	$\frac{5}{55}=9.1\%$	$\frac{47}{55}=85.3\%$
		100,000	$\frac{3}{55}=5.6\%$	$\frac{5}{55}=9.1\%$	$\frac{47}{55}=85.3\%$
		150,000	$\frac{2}{55}=3.6\%$	$\frac{7}{55}=12.7\%$	$\frac{46}{55}=83.7\%$

Table 3 Experimental results for general BP net



(a)the Special net in our experiment (b)General BP net

Fig. 6 Curves for mean square error

V. Conclusion

In this paper, a new way of weight connection is adopted and a new algorithm for error back propogation is deduced based upon general BP algorithm. Our network has an excellent performance and a rapid convergence speed which is noticeably superior to general BP network. Satisfactory results is obtained in our application to car shape recognition. Though our basic idea about learning algorithm inherits that about traditional BP algorithm and local minimization problem is not satisfactorily solved, our research work, as an application technology, is of great importance to theoretical study on neural network and development of pattern recognition techniques.

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